Artificial intelligence and internet of things in manufacturing decision processes

Article *in* IAES International Journal of Artificial Intelligence (IJ-AI) · June 2024

DOI: 10.11591/ijai.v13.i2.pp2185-2200

Santo Wijaya
Meta Industry Polytechnic

Fransisca Debora
University of Singaperbangsa Karawang

Arief Ramadhan
Telkom University

IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 13, No. 2, June 2024, pp. 2185∼2200
ISSN: 2252-8938, DOI: 10.11591/ijai.v13.i2.pp2185-2200

Artificial intelligence and internet of things in manufacturing decision processes

Santo Wijaya[1], Lim Hermanto Rudy[2,3], Fransisca Debora[4], Rana Ardila Rahma[4], Arief Ramadhan[5], Yusita Attaqwa[6]
[1]Department of Software Engineering, Polytechnic META Industry Cikarang, Bekasi, Indonesia
[2]Suzhou Kunlene Film Industries Co. Ltd., Suzhou, China
[3]Yunnan Kunlene Film Industries Co. Ltd., Kunming, China
[4]Department of Industrial Engineering, Faculty of Engineering, Singaperbangsa University of Karawang, Indonesia
[5]School of Computing, Telkom University, Bandung, Indonesia
[6]Department of Industrial Engineering, Polytechnic META Industry Cikarang, Bekasi, Indonesia

Article Info

Article history:

Received Jun 28, 2023
Revised Oct 9, 2023
Accepted Dec 16, 2023

Keywords:

Artificial intelligence
Internet of things
Manufacturing systems
Smart-decision process
Systematic review

ABSTRACT

This paper explores the influence of the internet of things (IoT) and artificial intelligence (AI) on the decision-making processes of modern manufacturing systems. With the proliferation of IoT devices and the development of AI technologies, manufacturing companies increasingly leverage these technologies to improve their decision-making abilities. This study aims to investigate the potential benefits, difficulties, and ramifications of integrating IoT and AI in manufacturing systems. The review employs the preferred reporting items for systematic reviews and meta-analyses (PRISMA) method with a systematic mapping process with four research questions. A total of 1282 articles were collected between 2017 and 2023, reviewed in accordance with the inclusion and exclusion criteria, and 66 articles were chosen. The research on IoT and AI technologies influentially affects other research in the production control layer manufacturing area based on the top-ten cited articles. In contrast, the research in this area focused on the operations management layer, specifically manufacturing analytics processes. This paper's findings contribute to a greater understanding of the impact of IoT and AI on decision-making in modern multi-domain manufacturing systems and provide direction for future research in this field.

Corresponding Author:

Santo Wijaya
Department of Software Engineering, Polytechnic Meta Industry Cikarang
Jln. Inti I Blok C1 No. 7, Lippo Cikarang, Bekasi, Indonesia
Email: santo.wijaya@politeknikmeta.ac.id

1. INTRODUCTION

Emerging technologies such as the internet of things (IoT) and artificial intelligence (AI) are undergoing a transformative phase as enablers. They could potentially revolutionize decision-making processes in modern manufacturing systems [1]. IoT refers to the connectivity of devices on the internet or in a local network. The IoT enables the seamless integration of physical devices, sensors, and systems, thereby facilitating the collection and transmission of real-time data. On the other hand, AI involves computer systems performing intelligent tasks by imitating human behavior and thinking. It can be categorized as weak AI or strong AI, with weak AI being commonly used in practical applications to solve specific problems effectively [2]. AI domains, such as machine learning, enable the analysis of vast amounts of data and the extraction of insightful

information to perform predictive analytics; planning and optimization enable lean production systems; computer vision (CV) improves quality check systems; and several other AI technologies have proven useful for industrial applications [3].

IoT refers to the connectivity of devices on the internet or in a local network. Typically, IoT is implemented using a cloud-based or cloud-edge-based architecture that collects data from multiple sources [4]. Recent developments in low power wide area network (LPWAN) communication standards explicitly designed for IoT applications have enhanced the capabilities of the systems further [5]. On the other hand, the collection of big data has enabled the creation of a virtually physical system known as the digital twin (DT), which is the key to enhancing the value of IoT [6]. In addition, implementing IoT systems will enable the seamless integration of cyber-physical systems (CPS) and fundamentally transform human-machine interaction. Middleware, typically defined as a software system designed to serve as an intermediary between IoT devices and applications, is a crucial technology in the realization of IoT systems [7].

AI involves computer systems performing intelligent tasks by imitating human behavior and thinking. It can be categorized as weak AI or strong AI, with weak AI being commonly used in practical applications to solve specific problems effectively [2]. The application of AI domains typically found in manufacturing systems includes machine learning (ML) and computer vision (CV). ML methods are divided into several classes depending on the learning method and purpose of the algorithm [8] and include the following techniques applied to specific manufacturing tasks: supervised learning (SL) [9], unsupervised learning (UL) or cluster analysis [10], semi-supervised learning (SSL) or reinforcement learning (RL) [11], and deep learning (DL) [12]. The integrated application of ML and CV has facilitated the implementation of previously complex control tasks and accurate quality check systems in various manufacturing fields [13].

Manufacturers increasingly utilize the IoT and AI to enhance their decision-making abilities and operational efficiencies. The development of smart manufacturing systems (SMSs) using these technologies is one of the manufacturing paradigm roadmaps to address global competition and customization needs [14]. Smart decision processes in SMSs enabled by IoT and AI allow manufacturers to make more informed and timely decisions, optimize production processes, support continuous improvement processes, and address supply chain management challenges. Sustainable products and services compel SMSs to reengineer their business models to be more intelligent, resulting in value co-creation for stakeholders. According to ISA95 [15], the business requirements model has three layers: business planning and logistics, operations management, and production control. In this work, we adopted the classification of each business requirements model by Qu *et al.* [16] as a reference to cluster types of smart decision processes in manufacturing systems.

Much research has been published in IoT and AI technologies development to enhance SMSs. There have been several survey papers related to this field. Zheng *et al.* [14] explore SMSs with integrated Industry 4.0 technologies like IoT, AI, big data, and blockchain. The review highlights key technologies in a conceptual framework and demonstrative scenarios for smart design, machining, control, monitoring, and scheduling. Qu *et al.* [16] emphasizes the need for a unified definition and analysis of requirements for SMSs to guide the transformation of traditional manufacturing enterprises into intelligent ones. The paper comprehensively overviews SMSs, including their evolution, objectives, functional and technical requirements, and components. Hansen and Bøgh [17] explore the adoption of IoT and AI in small and medium-sized manufacturing enterprises (SMEs) and provide an overview of enablers and analytics capabilities. The study summarizes emerging research and strategies to make AI and IoT accessible to SMEs. However, as far as the authors are aware, there has not been a comprehensive review that explicitly explores the advancements in IoT and AI technologies within multi-domain manufacturing systems and their impact on decision-making processes.

This study, therefore, with the following five-fold contributions, presents a systematic literature review (SLR) of the research articles published between the years 2018 and 2023: i) a detailed approach has been developed to conduct a thorough and systematic search using a revised study mapping process consisting of six distinct phases; ii) the study presents information regarding the intensity of publications and entities that actively conduct the research in the domain; iii) this paper contributes to the identification of key technologies in IoT, AI, and their combinations that enhance smart decision processes in multi-domain manufacturing systems; iv) in addition, we summarize comprehensive mapping type of decision processes utilize these technologies and its' ramifications; v) the review delivers a thorough body of knowledge and the current state of this particular field. The paper identifies the research gaps, problems, and challenges that need further research for possible future directions.

2. METHOD

This SLR aims to compile a comprehensive list of all decision-making processes in manufacturing systems based on IoT and AI studies published in the scientific literature between 2017 and 2023. The guidelines followed in this paper are taken from the SLR published in [18], which is a combination of the preferred reporting items for systematic reviews and meta-analyses (PRISMA) statement [19] and the systematic mapping process presented in [20]. We modified the mapping process into six phases, namely a (P1) preliminary study, (P2) formulation of research questions, (P3) identification of search criteria, then, from all papers found in a literature search, a (P4) screening process, (P5) availability and eligibility assessment of the selected studies, (P6) data extraction and compilation as shown in Figure 1.

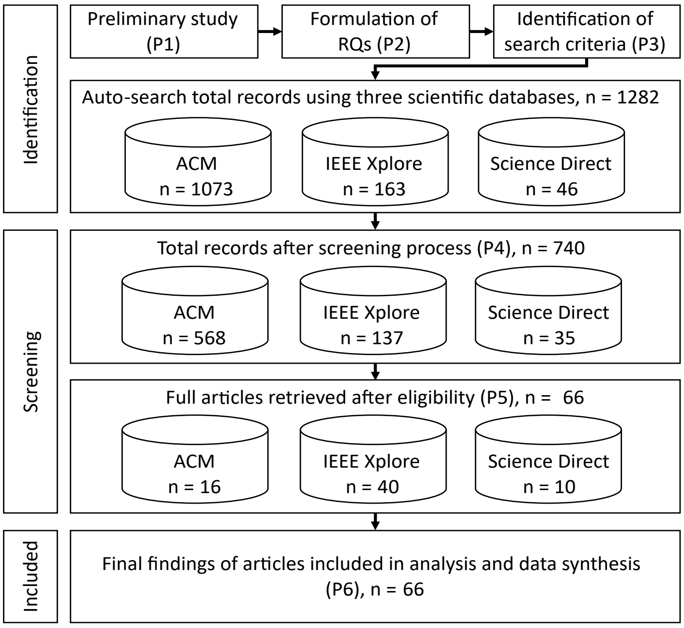

Figure 1. SLR protocol for selection of the articles

In the preliminary study (P1), the search areas are refined by gathering background information on studies on IoT and AI's impact on manufacturing system's decision-making processes. In this case, a random search on the most popular search engine, Google Scholar, was conducted using a single domain-specific keyword, such as IoT or AI-based manufacturing systems. Then, we filtered out the search results and focused on the studies that helped us formulate the review's objective.

The formulation of research questions (P2), as the means to achieve the objective, utilizes the population, intervention, and context (PiCO) tools adopted from Pollock and Berge [21], which consists of three elements: population, interest, and context. The population of this research is IoT and AI technologies; the interests are the potential benefits, difficulties, and ramifications of integrating IoT and AI in manufacturing systems and the context of decision-making processes in modern manufacturing systems. Therefore, based on the PiCO tool-defined elements, the three research questions (RQs) are as follows:

– RQ1: What is the intensity of publications in the domain in terms of year and country?
– RQ2: What articles rank and topic in the top ten in terms of total citations?
– RQ3: Which IoT and AI technologies are used in the decision-making processes in modern manufacturing systems?
– RQ4: What type of manufacturing system decision-making process utilizes IoT and AI technologies?

Then, search criteria (P3) are identified to enhance the database's search features so that relevant articles can be located systematically for the review. The primary indexed databases selected for this study are the IEEE Xplore, Science Direct, and ACM Digital Library. These databases offer a wide range of engineering and computer science research papers, making them reliable choices for researchers in these fields. While SCOPUS and other databases also provide valuable research resources, the selected databases are frequently chosen due to their reputation, comprehensiveness, and specialization in engineering and computer science domains.

Based on the RQs, the search strings used to apply the automatic search in the selected databases are as follows: ("decision-making processes" OR "decision process" OR "decision") AND ("manufacturing systems" OR "manufacturing") AND ("artificial intelligence" OR "machine learning") AND ("internet of things" OR "IoT"). This approach successfully retrieved 163 IEEE Explore articles, 46 Science Direct articles, and 1073 ACM Digital Library articles.

In the screening process (P4), the 1282 retrieved articles were filtered using the article selection criteria. The inclusion criteria are article publication year between 2018 and 2023, English-written article, article published only in a journal or conference, and primary research article. The exclusion criteria are those that do not meet the inclusion criteria, and duplicate articles are removed from the list. Five hundred forty-two articles were removed, and we obtained 740 through screening.

In the next phase (P5), assessing the availability and eligibility of the primary studies obtained in the previous phase is critical. This survey conducts an availability assessment and collects all of the article's full text. Then we adopted the eligibility criteria (EC) mentioned in [22], including the quality score and its rubric description, as follows:

a) EC1: the terms used in search strings are mentioned in the article's title, abstract, or keywords;
   - Score = 1, if it clearly mentions the search strings,
   - Score = 0.5, if it mentions the search strings partly,
   - Score = 0, if it does not mention the search strings.
b) EC2: the study scope is in the manufacturing areas;
   - Score = 1, if it clearly considers the research problem in the specific manufacturing area,
   - Score = 0.5, if it considers the research problem in the general manufacturing area,
   - Score = 0, if it does not consider the research problem in the manufacturing area.
c) EC3: the objectives of the study are well-defined;
   - Score = 1, if it clearly defines and follows the objectives of the study,
   - Score = 0.5, if it defines the objectives of the study but is not clearly followed,
   - Score = 0, if it does not define the objectives nor clearly described research.
d) EC4: clear methodology and experimentation process;
   - Score = 1, if it clearly explains the methodology and experimentation process,
   - Score = 0.5, if it describes the methodology but provides no detailed experimentation process,
   - Score = 0, if it does not describe the methodology nor the experimentation process.
e) EC5: the findings are mentioned clearly and relate to the objective;
   - Score = 1, if it clearly explains the findings and relates to the objective,
   - Score = 0.5, if it explains the findings but partly relates to the objective,
   - Score = 0, if it does not mention the finding.
f) EC6: the limitations of the study are well acknowledged.
   - Score = 1, if it clearly mentions the limitations of the study,
   - Score = 0.5, if it mentions the limitations but not in detail,
   - Score = 0, if the study's limitations are not well-acknowledged.

Based on the ECs that have been determined, this study assesses all of the 740 selected articles, and if there is a score value of 0 on one of the criteria, then the article was excluded from the lists. In this phase, 674 articles were removed, and 66 articles were obtained for the final phase. The articles consist of the following references [23–87].

Lastly, we performed data extraction and compilation (P6) to review and compare the articles after properly categorizing them to be included in the systematic literature survey using the P4 and P5 steps. Microsoft Excel [88] is used to record information from the publications and accomplish the paper's objectives. Title, abstract, keywords, authors, publication year, publisher, publication type, total citations, research problems, proposed method, results, limitations, and future research were all extracted from each included article.

Then, we aggregate and cluster the extracted data into types of IoT technologies (e.g., hardware, software, architecture), types of AI technologies (e.g., machine vision, ML, planning, and optimization), types of manufacturing industries, types of decision processes, and types of data analytics used.

3. RESULTS AND DISCUSSION

3.1. Answering RQ1: The intensity of research in terms of publication year-wise and country-wise

This study focuses on publications from 2018 to 2023, specifically exploring the IoT and AI technologies implementation in SMSs. Figure 2 illustrates the number of studies conducted during this period segmented by their publication type (conference and journal), with the highest number of publications in 2020 (21 studies). The number of articles has gradually increased, with only five studies in 2018 and 19 studies in 2019. However, there has been a decline in 2021 and 2022, possibly due to the impact of the COVID-19 pandemic on conferences and research activities. On the other hand, 2023 is not counted as a full year yet, as this research was conducted between May and June 2023. Despite this, the overall trend indicates a growing popularity of research in this domain.

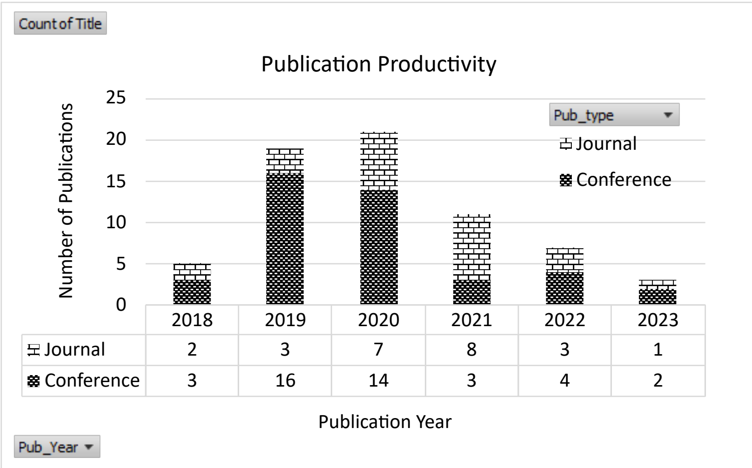

Figure 2. Publication productivity between 2018 and 2023

Figure 3 shows country-wise research publication and impact index. The country is based on the first author's country of affiliation. There are a total of 29 countries in the 66 reviewed articles. China published the most research with 16 articles, followed by the USA and Germany with five articles, respectively. Moreover, we calculate the impact index based on the total articles divided by the total citations for each country to investigate influential research country-wise. The top three countries with the most publications have similar impact indexes, with Germany, China, and the USA leading. Interestingly, the top three countries with the highest impact index are Saudi Arabia, Turkey, and Denmark. Even though these countries only have one publication, it was cited in many articles.

3.2. Answering RQ2: Articles rank and topic in the top ten in terms of total citations

Table 1 shows the top-ten cited articles based on total citations obtained on May 29th, 2023. IEEE, three by Science Direct, published six articles, and only one by ACM in the top ten cited articles. China published one article with four different affiliations, while Saudi Arabia, Turkey, Italy, Germany, the USA, and Taiwan published one article. The top ten most cited articles mainly originated from technologically advanced countries, such as China, the USA, Germany, Taiwan, and Italy. Regarding total citations, Tang *et al.* [42] received the most with 101 total citations. On the other hand, in terms of citations per year, He *et al.* [60] has the highest with 44 citations per year. Moreover, the top-ten articles each have distinct topics related to flexible agent-based systems [42], cloud-edge architecture for big data [28], robot hardware path planning [38], data anomaly detection and security [41], DT [83], [35], robotics [60], safety monitoring [66], predictive maintenance [59], and quality prediction analysis [56].

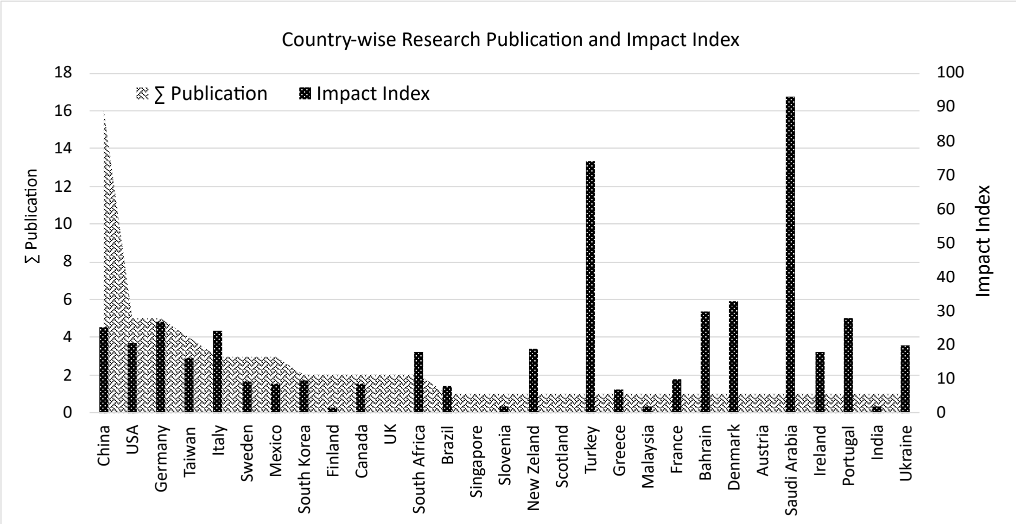

Figure 3. Country-wise publication and impact index between 2018 and 2023

Table 1. Top-ten cited articles based on total citations

Rank	Ref.	Publisher	Year	Country	Affiliation	Citations	Citations/Year
1	[42]	IEEE	2018	China	South China University of Tech.	101	20.2
2	[41]	IEEE	2020	Saudi Arabia	University of Bisha	93	31.0
3	[60]	Science Direct	2021	China	Chang'an University	88	44.0
4	[66]	Science Direct	2021	Turkey	Iskenderun Technical University	74	37.0
5	[59]	Science Direct	2019	Italy	Politecnico di Torino	65	16.3
6	[83]	ACM	2020	Germany	RWTH Aachen University	64	21.3
7	[28]	IEEE	2020	China	Beijing Institute of Tech.	54	18.0
8	[56]	IEEE	2020	China	Beihang University	52	17.3
9	[35]	IEEE	2020	USA	National Institute of Standards and Tech.	49	9.8
10	[38]	IEEE	2021	Taiwan	National Taiwan University	47	23.5

3.3. Answering RQ3: IoT and AI technologies that are used in the decision-making processes in SMSs

We summarize the IoT and AI technologies considered in the study of SMSs as shown in Table 2. First, the technology considered in the study is clustered into three domains: the proposed study with integrated IoT and AI technologies, the proposed study with only IoT technology, and the proposed study with only AI technology. Then, it summarized each IoT and AI technology type, with its domain mapped to each article. There are 41 articles proposed with IoT and AI technology, 14 with only IoT technology, and 11 with only AI technology.

This study also explores the correlation between the AI and IoT domains in their implementation in industries, as shown in Figure 4. Based on the result, the agent-based system in the AI domain is mostly considered together with the DT/CPS method in the IoT domain, as indicated by four articles. CV and robotics automation in the AI domain are considered together with the hardware/sensor networks and software/middleware/API in the IoT domain, as indicated by one article. As indicated by ten articles, ML in the AI domain is mostly utilized in the hardware/sensor networks of the IoT domain. On the other hand, the planning and optimization in the AI domain are utilized together with cloud/fog/edge architecture and DT/CPS in the IoT domain, as indicated by the two articles, respectively.

3.4. Answering RQ4: Type of manufacturing system decision-making process utilizes IoT and AI technologies

We have summarized 41 articles that do not specify specific industries in the discussion. While the rest of the articles defined specific industries, and this review categorized them into 14 types of industries, such as aero-engine [43], automotive [32], [33], electronics [23], [39], [77], fast-moving consumer goods [69], garment [30], machining [62], [67], [68], [76], [80], [82], metallurgies [78], [79], [63], milling [26], [59], oil

and gas [50], semiconductor [49], water treatment plant [73], tobacco [86], transportation [54], small-medium enterprises [52]. The correlation between IoT and AI technologies with the categorized industries type is shown in Figure 5.

Table 2. Summary of IoT and AI technologies considered in the study of SMSs

Description	Technology Domain	Reference	Total Study
Proposed Domain	IoT and AI	[23–25, 27, 29, 31, 33, 34, 37, 38, 41–49, 53, 54]	41
		[56–62, 64–67, 70, 74, 76, 77, 80–82, 87, 89]	
	IoT only	[28, 30, 35, 36, 40, 50–52, 55, 72, 75, 83, 84, 86]	14
	AI only	[26, 32, 39, 63, 68, 69, 71, 73, 78, 79, 85]	11
AI Domain	AI-1. Agent-based Systems	[29, 42, 58, 61, 89]	5
	AI-2. CV	[76, 80]	2
	AI-3. ML	[23, 25–27, 31–34, 37, 39, 41, 44–47, 53, 54, 56, 57]	35
		[59, 62, 63, 65–68, 71, 73, 74, 77–79, 81, 82, 87]	
	AI-4. Planning & Optimization	[24, 38, 43, 48, 49, 69, 70, 85]	8
	AI-5. Robotics & Automation	[60, 64]	2
IoT Domain	IoT-1. Cloud/ Fog/ Edge Architecture	[27–30, 34, 36, 42, 44, 49, 52, 55, 56, 70, 86]	14
	IoT-2. Cyber Security/ Cyber Threat	[37, 41, 50, 51, 75, 82, 84]	7
	IoT-3. DT/ CPS	[24, 35, 42, 48, 53, 58, 61, 65, 67, 83, 87, 89]	12
	IoT-4. Hardware/ Sensor Networks	[31, 33, 38, 47, 54, 57, 59, 60, 62, 74, 77, 80, 81]	13
	IoT-5. Software/ Middleware/ API	[23, 25, 40, 43, 45, 46, 64, 66, 72, 76]	10

	Agent-based Systems	Computer Vision	Machine Learning	Planning & Optimization	Robotics & Automation
Hardware/ Sensor Networks		1	10	1	1
Software/ Middleware/ API		1	5	1	1
Security/ Cyber Security/ Threat			3		
Cloud/ Fog/ Edge Architecture	1		4	2	
Digital Twin/ Cyber Physical Systems	4		4	2	

Figure 4. Correlation between AI and IoT technologies

	Agent-based Systems	Computer Vision	Machine Learning	Planning & Optimization	Robotics & Automation	Cloud/ Fog/ Edge Architecture	Digital Twin/ Cyber Physical Systems	Hardware / Sensor Networks	Security/ Cyber Security/ Threat	Software/ Middleware/ API
			AI					IoT		
16_Water Treatment Plant	0	0	1	0	0	0	0	0	0	0
15_Transportation (Locomotive)	0	0	1	0	0	0	0	1	0	0
14_Tobacco	0	0	0	0	0	1	0	0	0	0
13_Steel Manufacturing	0	0	1	0	0	0	0	0	0	0
12_SMEs	0	0	0	0	0	1	0	0	0	0
11_Semiconductor	0	0	0	1	0	1	0	0	0	0
10_Oil and Gas	0	0	0	0	0	0	0	0	1	0
9_Milling	0	0	2	0	0	0	0	1	0	0
8_Metallurgies	0	0	2	0	0	0	0	0	0	0
7_Machining	0	2	4	0	0	0	1	2	1	1
6_General	5	0	19	5	2	9	11	7	5	7
5_Garment	0	0	0	0	0	1	0	0	0	0
4_Fast Moving Consumer Goods	0	0	1	0	0	0	0	0	0	0
3_Electronics	0	0	3	0	0	0	0	1	0	1
2_Aeroengine	0	0	0	1	0	0	0	0	0	1
1_Automotive	0	0	2	0	0	0	0	1	0	0

Figure 5. Correlation between AI and IoT technologies with the categorized industries type

According to ISA95 [15], there are three layers of the business requirements model: business planning and logistics (BPL), operations management (OM), and production control (PC). In this work, we adopted the classification of each business requirements model by Qu *et al.* [16] as a reference to cluster types of smart decision processes in manufacturing systems. From Figure 6, it can be concluded that decision-making utilizing IoT and AI technologies is predominantly used in operations management, specifically in manufacturing analytics processes in the form of simulation, descriptive research, and applied research, as indicated by 27 articles. On the other hand, these technologies are mostly utilized for planning and control processes in the business plans and logistics layer, as indicated by 13 articles. In the production control layer, quality management and smart machines with advanced robotics processes share the same article's contribution, as indicated by 11 and 10 articles, respectively. We also correlate the IoT and AI technologies with each decision process type to have better insights in reviewing the literature, as shown in Figure 7. The successful implementation of IoT and AI technologies in operations management, especially for manufacturing analytics, has resulted in significant process improvements, enhancements, and evaluations, as described in Table 3. However, we only mention the articles that consider IoT and AI technologies in manufacturing analytics processes due to space constraints.

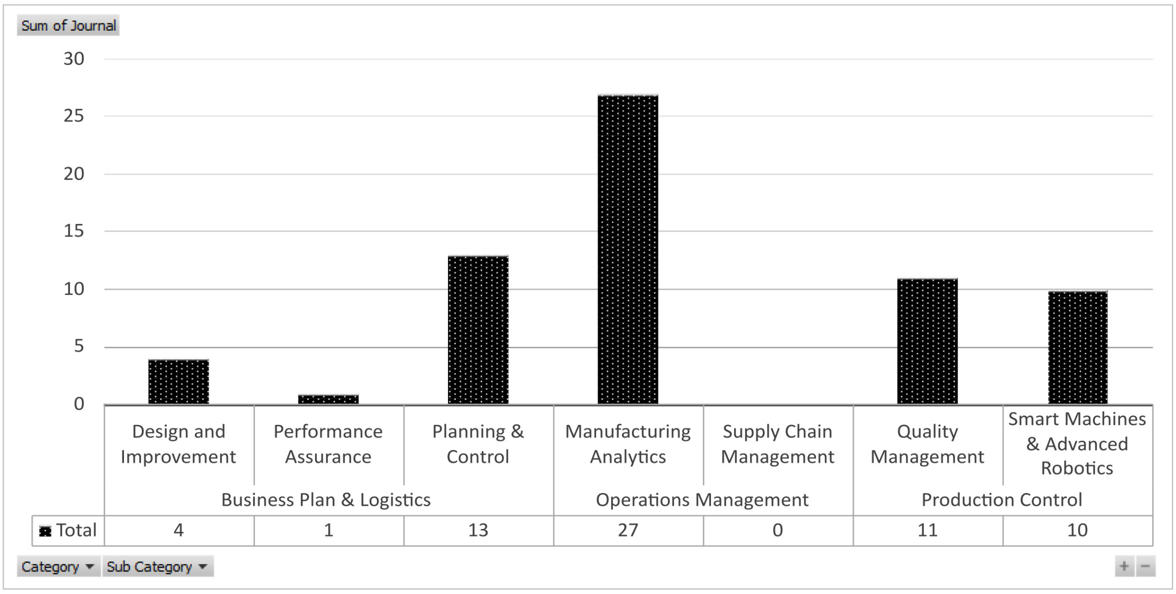

Figure 6. Types of decision process utilized IoT and AI technologies

	Agent-based Systems	Computer Vision	Machine Learning	Planning & Optimization	Robotics & Automation	Cloud/ Fog/ Edge Architecture	Digital Twin/ Cyber Physical Systems	Hardware/ Sensor Networks	Security/ Cyber Security/ Threat	Software/ Middleware/ API
	AI					IoT				
PC - Smart Machines & Advanced Robotics	2	2	4	2	0	1	3	3	2	1
PC - Quality Management	1	0	6	2	1	1	3	2	0	4
OM - Supply Chain Management	0	0	0	0	0	0	0	0	0	0
OM - Manufacturing Analytics	2	0	12	1	0	8	3	4	5	3
BPL - Planning & Control	0	0	10	2	0	2	2	2	0	1
BPL - Performance Assurance	0	0	1	0	0	1	0	0	0	0
BPL - Design & Improvement	0	0	3	0	1	0	1	2	0	1

Figure 7. Correlation between AI and IoT technologies with the types of decision process

Table 3. Implementation of IoT and AI technologies in operations management

Ref.	Research Problems	AI Tech.	IoT Tech.	Result	Method
[23]	Exploration of AI-related phenomena and ML in software and big data by conducting group discussions with software vendors.	AI-3	IoT-5	Utilize much data to support real-time decision-making within organizations undergoing digital transformation.	Descriptive
[27]	The traditional IoT schemes face challenges such as storing and managing large volumes of records, slow response times, and insufficient integration and utilization of information technology.	AI-3	IoT-1	The suggested solution involves employing Simple Additive Weighting and Analytic Hierarchy Processes to help overcome the limitations and improve decision-making in IIoT systems.	Applied
[29]	The enabling technologies support the relationship between the CMfg paradigm and the decision-making behavior of Manufacturing Services (MSs).	AI-1	IoT-5	Decision behaviors of MSs are positively influenced by the information transparency of the CMfg environment and the learning mechanism of MSs effects on the cooperative emergence.	Simulation
[33]	Design an intelligent information management system to provide predictive maintenance and improve decision support.	AI-3	IoT-4	The framework uses ML and signal processing techniques, AI algorithms, IoT devices, data mining and modeling techniques, rules and fuzzy logic systems, and advanced visualizations.	Descriptive
[43]	It is necessary to develop adequate data modeling and integration methods to manage and regulate the creation of the resulting big data.	AI-4	IoT-5	The method used is spatiotemporal modeling to organize data in temporal, spatial, and attributive dimensions applied to the modeling and integrating the IoT-generated MBD in the real shop floor.	Applied
[44]	How to avoid the human factor becoming a bottleneck of the entire production schedule.	AI-3	IoT-1	Combines domain ontology and RL to provide new ideas for scheduling and other practical problems in the manufacturing process.	Simulation
[47]	Importance to developing Maintenance Decision Support System (MDSS) for fault diagnostic and prognostic considering CM data along with event-triggered data.	AI-3	IoT-4	Training and testing accuracy for most models is higher than 90%. Optimal maintenance policies are centered on a time-dependent Proportional Hazards Model (PHM) coupled with a semi-supervised ML approach.	Simulation
[57]	Need for scalable data ranging from calibration capabilities for individual sensors with digital preprocessing output to quantification of uncertainties.	AI-3	IoT-4	A metrology framework for the full lifecycle of measured data in industrial applications.	Descriptive
[58]	Safety assurance concerns where operational data from sensors and actuators in the deployment area is fed back to the manufacturing process via the IoT infrastructure.	AI-1	IoT-3	A driven algorithm N-HyMn that infers non-linear hybrid automata representation from I/O operational as model-aware and model-agnostic to detect and evaluate potential safety threats.	Applied
[74]	Predictive maintenance (PdM) determines the optimal time point for maintenance actions based on the condition of the equipment. This task is becoming one of the most critical problems in systems management.	AI-3	IoT-4	A human-in-the-loop PdM approach in which a ML system predicts future problems in sets of workstations. The observed performance is sufficient to reduce the total number of user complaints by up to 50 percent.	Simulation
[82]	The existing research on secure 3D printing mostly focuses on nozzle kinetics, while attacks on filament kinetics and thermodynamics can also damage the printed object.	AI-3	IoT-2	Proposed a Sophos, a fine-grained and modular integrity-checking framework for FDM. It successfully detects filament-kinetic, and thermodynamic attacks.	Applied

3.5. Discussion

The overall trend indicates a growing popularity of research in this domain despite the COVID-19 pandemic, and IEEE is the publisher with the most selected articles in this field. China is the country with the most publications, but Saudi Arabia is the country with the highest impact index publication. The top ten most cited articles mainly originated from technologically mature countries, such as China, the USA, Germany, Taiwan, and Italy. Moreover, seven out of the top ten most cited articles consider the production control layer, in which [60], [66], [59], [56] proposed the IoT and AI technologies in quality management processes and [42], [38], [41] proposed these technologies in to develop smart machines with robotics processes. On the other hand, the findings found that the research in the field focused on the operations management layer in manufacturing analytics processes with 27 articles. Thus, the research on IoT and AI technologies influentially affects other research in the manufacturing area of the production control layer. In contrast, the research in this area focused on the operations management layer, specifically manufacturing analytics processes.

ML technology in the AI domain is currently the main area of research in this field, specifically neural network (NN) class. On the other hand, the IoT domain has a balance in using technology for smart decision processes in manufacturing systems. The development of AI technology has been a research trend in the last ten years, and the domains of AI technology are increasing exponentially due to the case-specific solutions provided by weak AI paradigms. We adopted the AI taxonomy introduced by Samoili *et al.* [90] to classify the types of AI technology domains in the study. The AI taxonomy aims to provide insights into the analysis of the AI landscape, aiming to identify AI applications in related fields like robotics, neuroscience, and the IoT. In summary, five domains of AI technology are identified as the findings of this literature review. In total, 35 articles considered the ML domain, eight articles considered the planning and optimization domain, five articles considered the agent-based systems domain and two articles considered the CV domain and the robotics and automation domain, respectively.

ML is currently one of the main areas of research, which is also in line with the findings of this study. ML techniques are categorized into several classes depending on how they are learned and what they are used for. UL, a branch of ML where a model learns patterns and structures in data without any explicit labeling or guidance from a predefined set of output labels, is considered in [27], [33], [46], [57], [59], [62], [78], [82]. UL in hardware/sensor networks and cloud/fog/edge architecture of IoT domain improves manufacturing analytics in operations management processes, especially to obtain better detection for condition monitoring of sensor-node [27], [57], machine anomalies [33], and alteration of transmitted manufacturing data [82].

SL, a branch of ML where a model learns from labeled training data to make accurate predictions or decisions on unseen data, is considered in [26], [63], [66], [74], [79]. Support vector machine (SVM), XGBoost, random forest, and Bayesian optimization are used particularly in predictive maintenance and condition monitoring in the discrete manufacturing process. The focus is on predicting the qualified workpiece rate, detecting devices and sensor's behaviors for IoT security and fault diagnosis, and optimizing an IIoT-based condition monitoring system with ML models for efficient predictive maintenance. It also highlights the criticality of predictive maintenance as a problem in systems management. It emphasizes the need for the adaptability of ML software systems to integrate new machines into existing systems.

RL, a branch of ML in which an agent learns to make sequential decisions through interactions with an environment, is considered in [44], [53], [54], [67], [77]. The research focused on the context of planning and control in the business plan and logistics industrial systems. It discusses the need to avoid the human factor becoming a bottleneck in production schedules and explores the application of RL in industrial CPS. It also presents a planning model for a mobile-based agent in a robot for material handling applications. It proposes a cyber-physical integration approach for online scheduling in smart factories.

Moreover, a type of ML technique inspired by the structure and functioning of the human brain, called NN, also received considerable attention. There were 11 articles, which are [31], [32], [34], [41], [56], [65], [69], [71], [73], [81], [87], found in this study. In the context of business plans and logistics decision processes, five articles address various challenges and research problems in improving production processes and decision-making using AI in Industry 4.0. The proposed methods include forecasting production plans, optimizing access to production resources through cloud additive manufacturing, effective resource schedules and secure data transmission in smart manufacturing, accurate prediction in industrial data analysis, integration of data mining techniques in continuous process industry systems, accurate forecast for mass customization, optimization of control systems in medical compressed air plants, detecting anomalous events in high-dimensional time series data, and reducing the computing and energy burden of DL models for heterogeneous devices. Moreover, in the context of production control decision processes, four articles address resource scheduling and secure data transmission, accurate prediction using quality features extracted from industrial data, integrating data mining techniques for improved reliability in continuous process industry systems, predicting mass customization to align customer demand with production capacity and inventory, optimizing control systems for energy efficiency in unmanned medical compressed air plants, detecting anomalous events in high-dimensional time series data while capturing complex inter-sensor relationships, reducing computing and energy burden for democratizing AI, and developing an adaptive model verification framework for modularized Industry 4.0 applications. On the other hand, three articles, which are [23], [25], [45], discussed ML in the general framework; two articles, which are [39], [68], utilized a statistical learning approach; one article, which is [47], used SSL.

A DT represents a virtual counterpart of a physical object or system, while a CPS combines physical components with digital systems to create interconnected and intelligent systems. DT can be a key component of CPS, providing a virtual representation for monitoring, analyzing, and optimizing physical processes. By

utilizing agent-based systems in DT and CPS, capturing the complexity and dynamics of the real-world scenario becomes possible. The agents can adapt to changing conditions, learn from experience, and provide intelligent decision-making capabilities [89], [42], [58], [61].

Moreover, the CV of the AI domain is considered together with the hardware/sensor networks of the IoT domain in [80], and the authors proposed a flexible production cell with artificial vision (AV) and an open-source computer numerical control (CNC) machine, Scorbot ER 4. The method successfully detects the position and orientation of rough material. CV is also considered together with the software/middleware/API of the IoT domain in [76], and the authors proposed the development of a CPS System (CPPS) that combines these technologies for autonomous path planning. The CPPS successfully moves chips from initial to goal states with minimal operator intervention.

Next, the planning and optimization of the AI domain are considered together with the IoT domain's cloud/fog/edge architecture in [49], [70]. Cloud architecture centralizes data storage and processing in remote servers, fog architecture distributes processing to the network edge, and edge architecture pushes computation directly to IoT devices. With the planning and optimization of the AI domain, each architecture offers distinct advantages in terms of scalability, real-time processing, and resource utilization, allowing for tailored solutions based on the specific use case. Ren *et al.* [70] proposed a data-centric approach to perform decentralized tiny ML and micro complex event processing (CEP) computation on IoT edge devices.

Lastly, the ML of the AI domain is mostly considered together with the hardware/sensor networks method of the IoT domain in ten articles. The UL class is used to provide condition monitoring to uncertainties of sensor output [57], to provide predictive maintenance of production equipment [59], [33], and to provide anomaly detection of machine health index [62]. The SL class is used to provide optimal time points for maintenance actions based on the condition of the equipment [74]. The RL class is used to provide a planning model of the mobile base agent of the SwarmItFIX robot with novel Swing and Dock (SaD) locomotion for material handling/transfer applications [54], and also combined with CV to create automated quality inspection in the production system [77]. The NN class is used as a model recommendation in the decision-making process [31], and combined with the compressive sensing (CS) method, enabling resource-efficient edge hardware intelligence [81]. Then, the SSL class is used to provide fault diagnostic and prognostic considering condition-based maintenance (CM) data along with event-triggered data [47].

In summary, although 41 articles consider the general type of manufacturing industries in their research, this review found that 14 types of multi-domain specific manufacturing industries were considered to utilize the IoT and AI technologies with good results. The articles mainly consider ML technologies in the AI domain with cloud/fog/edge architecture in the IoT domain for manufacturing analytics processes as it can provide insights and help smarter decisions to detect and classify problems earlier, and also increase manufacturing operations through prediction of production schedule or machine maintenance given big data from the manufacturing process. As current development considers weak AI approaches in the technologies, it is essential to develop especially the AI technology specific to the one domain of manufacturing area. The research in the specific manufacturing industry to develop solutions uniquely to that manufacturing problem with IoT and AI technologies could potentially be the future research direction.

4. CONCLUSION

By adhering to the standards of well-written SLR, this systematic literature survey aims to capture state-of-the-art research in the IoT and AI-based smart decision processes in manufacturing systems. As a result, this study used the PRISMA research method and a systematic mapping process with six phases. To lay the groundwork for this study, articles were extracted from the IEEE, Science Direct, and ACM databases to paint a complete picture of the research's current state between 2018 and 2023 to answer four RQs. Using the chosen keywords and search strings, 1282 articles were retrieved during the first stage of the primary search. To address the research questions of this systematic review, 66 studies in total were discovered during the screening process. Additionally, the apparent responses to the research questions assisted in identifying the knowledge gaps, problems, and difficulties in this field. Even though several literature reviews related to this field have been published, our study is the first to present a thorough and updated literature review. This systematic literature aimed to cover all papers published in the area and investigate and identify detailed IoT and AI technologies utilized in the smart decision process of multi-domain manufacturing systems by performing an in-depth analysis of the articles obtained from the literature. The research on IoT and AI technologies influentially

affects other research in the production control layer manufacturing area based on the top-ten cited articles. In contrast, the research in this area focused on the operations management layer, specifically manufacturing analytics processes. The articles mainly consider machine learning technology in the AI domain with cloud/ fog/ edge architecture in the IoT domain for manufacturing analytics processes as it can provide insights and help smarter decisions to detect and classify problems earlier, and also increase manufacturing operations through prediction of production schedule or machine maintenance given big data from the manufacturing process. However, there are some limitations to this systematic review. For instance, in this review, only studies published with minimum EC and written in English made it through the screening process. As a result, a few brief papers or publications might have been reported in another language and may have helped this field but have yet to be examined. The decision to exclude the papers above was made after carefully considering the eligibility requirements and the inclusion and exclusion criteria. Our analysis was primarily explanatory because the domain under consideration was so large. The goal was to evaluate the degree to which IoT and AI technologies are currently used and the potential they offer. It may contribute to addressing issues common in the decision-making process of manufacturing systems. Without determining the best, we have merely tracked which IoT and AI domains are used in which fields. Since the problems analyzed are so different and specific, comparing them reasonably would be difficult. Undoubtedly, more focused analysis and comparison could be made by restricting the scope and search strings (for example, to one of the classes mentioned in the paper, such as the machine learning - neural networks class of AI domain with the hardware/ sensor networks class of IoT domain), and this would be very beneficial for the continued development of the sector.

REFERENCES

[1] M. E. Porter and J. E. Heppelmann, "How smart, connected products are transforming companies," *Harvard Business Review*, vol. 2015, no. October, pp. 96–114, 2015.

[2] C. Pennachin and B. Goertzel, *Artificial General Intelligence*. Berlin, Heidelberg: Springer, 2007. doi: 10.1007/978-3-540-68677-4_1.

[3] A. Khanna and S. Kaur, "Internet of Things (IoT), Applications and Challenges: A Comprehensive Review," *Wireless Personal Communications*, vol. 114, no. 2, pp. 1687–1762, 2020. doi: 10.1007/s11277-020-07446-4.

[4] F. Tao, Q. Qi, A. Liu, and A. Kusiak, "Data-driven smart manufacturing," *Journal of Manufacturing Systems*, vol. 48, pp. 157–169, 2018. doi: 10.1016/j.jmsy.2018.01.006.

[5] K. Mekki, E. Bajic, F. Chaxel, and F. Meyer, "Overview of Cellular LPWAN Technologies for IoT Deployment: Sigfox, LoRaWAN, and NB-IoT," in *2018 IEEE International Conference on Pervasive Computing and Communications Workshops, PerCom Workshops 2018*. IEEE, 2018, pp. 197–202. doi: 10.1109/PERCOMW.2018.8480255.

[6] R. Minerva, G. M. Lee, and N. Crespi, "Digital Twin in the IoT Context: A Survey on Technical Features, Scenarios, and Architectural Models," *Proceedings of the IEEE*, vol. 108, no. 10, pp. 1785–1824, 2020. doi: 10.1109/JPROC.2020.2998530.

[7] A. H. Ngu, M. Gutierrez, V. Metsis, S. Nepal, and Q. Z. Sheng, "IoT Middleware: A Survey on Issues and Enabling Technologies," *IEEE Internet of Things Journal*, vol. 4, no. 1, pp. 1–20, 2017. doi: 10.1109/JIOT.2016.2615180.

[8] R. I. Mukhamediev, Y. Popova, Y. Kuchin, E. Zaitseva, A. Kalimoldayev, A. Symagulov, V. Levashenko, F. Abdoldina, V. Gopejenko, K. Yakunin, E. Muhamedijeva, and M. Yelis, "Review of Artificial Intelligence and Machine Learning Technologies: Classification, Restrictions, Opportunities and Challenges," *Mathematics*, vol. 10, no. 15, pp. 1–25, 2022. doi: 10.3390/math10152552.

[9] D. Zhang, B. Xu, and J. Wood, "Predict failures in production lines: A two-stage approach with clustering and supervised learning," in *2016 IEEE International Conference On Big Data (Big Data)*. IEEE, 2016, pp. 2070–2074. doi: 10.1109/BigData.2016.7840832.

[10] R.-J. Hsieh, J. Chou, and C.-H. Ho, "Unsupervised online anomaly detection on multivariate sensing time series data for smart manufacturing," in *2019 IEEE 12th Conference on Service-Oriented Computing and Applications (SOCA)*. IEEE, 2019, pp. 90–97. doi: 10.1109/SOCA.2019.00021.

[11] G. Kim, J. G. Choi, M. Ku, and S. Lim, "Developing a semi-supervised learning and ordinal classification framework for quality level prediction in manufacturing," *Computers and Industrial Engineering*, vol. 181, 2023. doi: 10.1016/j.cie.2023.109286.

[12] J. Wang, Y. Ma, L. Zhang, R. X. Gao, and D. Wu, "Deep learning for smart manufacturing: Methods and applications," *Journal of Manufacturing Systems*, vol. 48, pp. 144–156, 2018. doi: 10.1016/j.jmsy.2018.01.003.

[13] D. P. Penumuru, S. Muthuswamy, and P. Karumbu, "Identification and classification of materials using machine vision and machine learning in the context of industry 4.0," *Journal of Intelligent Manufacturing*, vol. 31, no. 5, pp. 1229–1241, 2020. doi: 10.1007/s10845-019-01508-6.

[14] P. Zheng, H. Wang, Z. Sang, R. Y. Zhong, Y. Liu, C. Liu, K. Mubarok, S. Yu, and X. Xu, "Smart manufacturing systems for Industry 4.0: Conceptual framework, scenarios, and future perspectives," *Frontiers of Mechanical Engineering*, vol. 13, no. 2, pp. 137–150, 2018. doi: 10.1007/s11465-018-0499-5.

[15] B. Scholten and D. Brandl, *The Road to Integration: A Guide to Applying the ISA-95 Standards in Manufacturing, Second Edition*. Pennsylvania, USA: International Society of Automation, 2022.

[16] Y. J. Qu, X. G. Ming, Z. W. Liu, X. Y. Zhang, and Z. T. Hou, "Smart manufacturing systems: state of the art and future trends," *International Journal of Advanced Manufacturing Technology*, vol. 103, pp. 3751–3768, 2019. doi: 10.1007/s00170-019-03754-7.

[17] E. B. Hansen and S. Bøgh, "Artificial intelligence and internet of things in small and medium-sized enterprises: A survey," *Journal of Manufacturing Systems*, vol. 58, pp. 362–372, 2021. doi: 10.1016/j.jmsy.2020.08.009.

[18] N. Talpur, S. J. Abdulkadir, H. Alhussian, M. H. Hasan, N. Aziz, and A. Bamhdi, "Deep Neuro-Fuzzy System application trends, challenges, and future perspectives: A systematic survey," *Artificial intelligence review*, vol. 56, no. 2, pp. 865–913, 2023.

[19] D. Moher, A. Liberati, J. Tetzlaff, D. G. Altman, and P. Group*, "Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement," *Annals of internal medicine*, vol. 151, no. 4, pp. 264–269, 2009. doi: 10.1136/bmj.b2535.

[20] K. Hussain, M. N. Mohd Salleh, S. Cheng, and Y. Shi, "Metaheuristic research: a comprehensive survey," *Artificial Intelligence Review*, vol. 52, pp. 2191–2233, 2019.

[21] A. Pollock and E. Berge, "How to do a systematic review," *International Journal of Stroke*, vol. 13, no. 2, pp. 138–156, 2018. doi: 10.1177/1747493017743796.

[22] N. F. Hordri, A. Samar, S. S. Yuhaniz, and S. M. Shamsuddin, "A systematic literature review on features of deep learning in big data analytics," *International Journal of Advances in Soft Computing and its Applications*, vol. 9, no. 1, pp. 32–49, 2017.

[23] S. Ahmed and S. Miskon, "IoT Driven Resiliency with Artificial Intelligence, Machine Learning and Analytics for Digital Transformation," in *2020 International Conference on Decision Aid Sciences and Application, DASA 2020*. IEEE, 2020, pp. 1205–1208. doi: 10.1109/DASA51403.2020.9317177.

[24] V. Kharchenko, O. Illiashenko, O. Morozova, and S. Sokolov, "Combination of Digital Twin and Artificial Intelligence in Manufacturing Using Industrial IoT," in *2020 IEEE 11th International Conference on Dependable Systems, Services and Technologies (DESSERT)*. IEEE, 2020, pp. 196–201. doi: 10.1109/DESSERT50317.2020.9125038.

[25] M. A. M. Ali, A. Basahr, M. R. Rabbani, and Y. Abdulla, "Transforming Business Decision Making with Internet of Things (IoT) and Machine Learning (ML)," *2020 International Conference on Decision Aid Sciences and Application (DASA)*, pp. 674–679, 2020. doi: 10.1109/DASA51403.2020.9317174.

[26] Y. Bei, Y. Zhou, X. Cheng, and E. Liu, "Qualified rate prediction of typical workpieces in discrete manufacturing process," in *Proceedings - 2020 International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering, ICBAIE 2020*. IEEE, 2020, pp. 409–412. doi: 10.1109/ICBAIE49996.2020.00092.

[27] G. Rathee, F. Ahmad, R. Iqbal, and M. Mukherjee, "Cognitive Automation for Smart Decision-Making in Industrial Internet of Things," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 3, pp. 2152–2159, 2021. doi: 10.1109/TII.2020.3013618.

[28] C. Yang, S. Lan, L. Wang, W. Shen, and G. G. Huang, "Big data driven edge-cloud collaboration architecture for cloud manufacturing: A software defined perspective," *IEEE Access*, vol. 8, pp. 45 938–45 950, 2020. doi: 10.1109/ACCESS.2020.2977846.

[29] P. Lou, J. Hu, C. Zhu, J. Yan, and L. Yuan, "Cooperation Emergence of Manufacturing Services in Cloud Manufacturing with Agent-Based Modeling and Simulating," *IEEE Access*, vol. 9, pp. 24 658–24 668, 2021. doi: 10.1109/ACCESS.2021.3055587.

[30] J. Liu, H. Cui, Y. Yang, and Y. Qiao, "Design of cloud platform for clothing intelligent manufacturing based on RFID technology," in *Proceedings - 2019 34rd Youth Academic Annual Conference of Chinese Association of Automation, YAC 2019*. IEEE, jun 2019, pp. 585–588. doi: 10.1109/YAC.2019.8787613.

[31] N. Contuzzi, A. Massaro, I. Manfredonia, A. Galiano, and B. Xhahysa, "A decision making process model based on a multilevel control platform suitable for industry 4.0," in *2019 IEEE International Workshop on Metrology for Industry 4.0 and IoT, MetroInd 4.0 and IoT 2019 - Proceedings*. IEEE, 2019, pp. 127–131. doi: 10.1109/METROI4.2019.8792854.

[32] W. B. Du, Z. Zhu, C. Wang, and Z. Yue, "The real-time big data processing method based on LSTM for the intelligent workshop production process," in *2020 5th IEEE International Conference on Big Data Analytics, ICBDA 2020*. IEEE, 2020, pp. 63–67. doi: 10.1109/ICBDA49040.2020.9101345.

[33] T. Vafeiadis, A. Nizamis, K. Apostolou, V. Charisi, I. N. Metaxa, T. Mastos, D. Ioannidis, A. Papadopoulos, and D. Tzovaras, "Intelligent information management system for decision support: application in a lift manufacturer's shop floor," in *IEEE International Symposium on INnovations in Intelligent SysTems and Applications, INISTA 2019 - Proceedings*. IEEE, 2019, pp. 1–6. doi: 10.1109/INISTA.2019.8778290.

[34] F. Mashhadi and S. A. Salinas Monroy, "Deep Learning for Optimal Resource Allocation in IoT-enabled Additive Manufacturing," in *2020 IEEE 6th World Forum on Internet of Things (WF-IoT)*. IEEE, 2020, pp. 1–6. doi: 10.1109/WF-IoT48130.2020.9221038.

[35] G. Shao and D. Kibira, "Digital manufacturing: requirements and challenges for implementing digital surrogates," in *2018 Winter Simulation Conference (WSC)*. IEEE, 2018, pp. 1226–1237. doi: 10.1109/WSC.2018.8632242.

[36] R. Hamzeh, R. Zhong, X. W. Xu, E. Kajati, and I. Zolotova, "A Technology Selection Framework for Manufacturing Companies in the Context of Industry 4.0," in *2018 World Symposium on Digital Intelligence for Systems and Machines (DISA)*. IEEE, 2018, pp. 267–276. doi: 10.1109/DISA.2018.8490606.

[37] C.-W. Tien, T.-Y. Huang, P. C. Chen, and J.-H. Wang, "Automatic device identification and anomaly detection with machine learning techniques in smart factories," in *2020 IEEE International Conference on Big Data (Big Data)*. IEEE, 2020. doi: 10.1109/bigdata50022.2020.9378168.

[38] K.-C. Chen, S.-C. Lin, J.-H. Hsiao, C.-H. Liu, A. F. Molisch, and G. P. Fettweis, "Wireless networked multirobot systems in smart factories," *Proceedings of the IEEE*, vol. 109, no. 4, pp. 468–494, 2021. doi: 10.1109/jproc.2020.3033753.

[39] J. Lyu, C. W. Liang, and P. S. Chen, "A data-driven approach for identifying possible manufacturing processes and production parameters that cause product defects: A thin-film filter company case study," *IEEE Access*, vol. 8, pp. 49 395–49 411, 2020. doi: 10.1109/ACCESS.2020.2974535.

[40] M. I. Ali, P. Patel, and J. G. Breslin, "Middleware for Real-Time Event Detection andPredictive Analytics in Smart Manufacturing," in *2019 15th International Conference on Distributed Computing in Sensor Systems (DCOSS)*. IEEE, 2019, pp. 370–376. doi: 10.1109/DCOSS.2019.00079.

[41] K. A. Abuhasel and M. A. Khan, "A Secure Industrial Internet of Things (IIoT) Framework for Resource Management in Smart Manufacturing," *IEEE Access*, vol. 8, pp. 117 354–117 364, 2020. doi: 10.1109/ACCESS.2020.3004711.

[42] H. Tang, D. Li, S. Wang, and Z. Dong, "CASOA: An Architecture for Agent-Based Manufacturing System in the Context of Industry 4.0," *IEEE Access*, vol. 6, pp. 12 746–12 754, 2017. doi: 10.1109/ACCESS.2017.2758160.

[43] W. Fang, Y. Guo, W. Liao, S. Huang, C. Yang, and K. Cui, "The spatio-temporal modeling and integration of manufacturing big data in job shop: an ontology-based approach," in *2020 IEEE 7th International Conference on Industrial Engineering and Applications (ICIEA)*. IEEE, 2020, pp. 394–398. doi: 10.1109/ICIEA49774.2020.9101999.

[44] S. Chen, J. Wang, H. Li, Z. Wang, F. Liu, and S. Li, "Top-down human-cyber-physical data fusion based on reinforcement learning," *IEEE Access*, vol. 8, pp. 134 233–134 245, 2020. doi: 10.1109/ACCESS.2020.3011254.

[45] F. Alves, H. Badikyan, H. J. Antonio Moreira, J. Azevedo, P. M. Moreira, L. Romero, and P. Leitao, "Deployment of a smart and predictive maintenance system in an industrial case study," in *2020 IEEE 29th International Symposium on Industrial Electronics*

(ISIE). IEEE, 2020, pp. 493–498. doi: 10.1109/ISIE45063.2020.9152441.

[46] S. Tamminen, X. Liu, H. Tiensuu, E. Ferreira, E. Puukko, and J. Roning, "AI Enhanced Alarm Presentation for Quality Monitoring," in *2018 IEEE International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData)*. IEEE, 2018, pp. 834–839. doi: 10.1109/Cybermatics_2018.2018.00162.

[47] K. Azar and F. Naderkhani, "Semi-supervised learning approach for optimizing condition-based-maintenance (CBM) decisions," in *2020 IEEE International Conference on Prognostics and Health Management (ICPHM)*. IEEE, 2020, pp. 1–6. doi: 10.1109/ICPHM49022.2020.9187022.

[48] Y. Ma, H. Zhou, H. He, G. Jiao, and S. Wei, "A digital twin-based approach for quality control and optimization of complex product assembly," in *2019 International Conference on Artificial Intelligence and Advanced Manufacturing (AIAM)*. IEEE, oct 2019, pp. 762–767. doi: 10.1109/AIAM48774.2019.00157.

[49] M. Khakifirooz, M. Fathi, and K. Wu, "Development of Smart Semiconductor Manufacturing: Operations Research and Data Science Perspectives," *IEEE Access*, vol. 7, pp. 108 419–108 430, 2019. doi: 10.1109/ACCESS.2019.2933167.

[50] E. A. Buhulaiga, A. Telukdarie, and S. J. Ramsangar, "Delivering on Industry 4.0 in a multinational petrochemical company: design and execution," in *2019 International Conference on Fourth Industrial Revolution (ICFIR)*. IEEE, 2019, pp. 1–6. doi: 10.1109/ICFIR.2019.8894790.

[51] Z. Zhang, L. Huang, R. Tang, T. Peng, L. Guo, and X. Xiang, "Industrial blockchain of things: a solution for trustless industrial data sharing and beyond," in *2020 IEEE 16th International Conference on Automation Science and Engineering (CASE)*. IEEE, 2020, pp. 1187–1192. doi: 10.1109/CASE48305.2020.9216817.

[52] M. Baritto, M. M. Billal, S. M. Muntasir Nasim, R. A. Sultana, M. Arani, and A. J. Qureshi, "Supporting tool for the transition of existing small and medium enterprises towards Industry 4.0," in *2020 International Conference on Data Analytics for Business and Industry: Way Towards a Sustainable Economy (ICDABI)*. IEEE, 2020, pp. 1–5. doi: 10.1109/ICDABI51230.2020.9325704.

[53] X. Liu, H. Xu, W. Liao, and W. Yu, "Reinforcement learning for cyber-physical systems," in *2019 IEEE International Conference on Industrial Internet (ICII)*. IEEE, 2019, pp. 318–327. doi: 10.1109/ICII.2019.00063.

[54] S. Veeramani and S. Muthuswamy, "Reinforcement learning based path planning of the mobile agents with constrained locomotion for the material handling applications," in *2020 IEEE 4th Conference on Information & Communication Technology (CICT)*. IEEE, 2020, pp. 1–5. doi: 10.1109/CICT51604.2020.9311923.

[55] J. Campos, P. Sharma, M. Albano, E. Jantunen, D. Baglee, and L. L. Ferreira, "Arrowhead framework services for condition monitoring and maintenance based on the open source approach," in *2019 6th International Conference on Control, Decision and Information Technologies (CoDIT)*. IEEE, 2019, pp. 697–702. doi: 10.1109/CoDIT.2019.8820366.

[56] L. Ren, Z. Meng, X. Wang, R. Lu, and L. T. Yang, "A Wide-Deep-Sequence Model-Based Quality Prediction Method in Industrial Process Analysis," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 31, no. 9, pp. 3721–3731, sep 2020. doi: 10.1109/TNNLS.2020.3001602.

[57] T. Dorst, B. Ludwig, S. Eichstadt, T. Schneider, and A. Schutze, "Metrology for the factory of the future: towards a case study in condition monitoring," in *2019 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*. IEEE, 2019, pp. 1–5. doi: 10.1109/I2MTC.2019.8826973.

[58] I. Lamrani, A. Banerjee, and S. K. S. Gupta, "Operational data-driven feedback for safety evaluation of agent-based cyber–physical systems," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 5, pp. 3367–3378, 2021. doi: 10.1109/TII.2020.3009985.

[59] E. Traini, G. Bruno, G. D'Antonio, and F. Lombardi, "Machine learning framework for predictive maintenance in milling," *IFAC-PapersOnLine*, vol. 52, no. 13, pp. 177–182, 2019. doi: 10.1016/j.ifacol.2019.11.172.

[60] R. He, M. Li, V. J. Gan, and J. Ma, "BIM-enabled computerized design and digital fabrication of industrialized buildings: A case study," *Journal of Cleaner Production*, vol. 278, pp. 1–13, 2021. doi: 10.1016/j.jclepro.2020.123505.

[61] F. Foukalas, "Cognitive IoT platform for fog computing industrial applications," *Computers & Electrical Engineering*, vol. 87, p. 106770, oct 2020. doi: 10.1016/j.compeleceng.2020.106770.

[62] M. Züfle, F. Moog, V. Lesch, C. Krupitzer, and S. Kounev, "A machine learning-based workflow for automatic detection of anomalies in machine tools," *ISA Transactions*, vol. 125, pp. 445–458, jun 2022. doi: 10.1016/j.isatra.2021.07.010.

[63] T. Nkonyana, Y. Sun, B. Twala, and E. Dogo, "Performance evaluation of data mining techniques in steel manufacturing industry," *Procedia Manufacturing*, vol. 35, pp. 623–628, 2019. doi: 10.1016/j.promfg.2019.06.004.

[64] C. Emeric, D. Geoffroy, and D. Paul-Eric, "Development of a new robotic programming support system for operators," *Procedia Manufacturing*, vol. 51, pp. 73–80, 2020. doi: 10.1016/j.promfg.2020.10.012.

[65] M. L. Hoffmann Souza, C. A. da Costa, G. de Oliveira Ramos, and R. da Rosa Righi, "A feature identification method to explain anomalies in condition monitoring," *Computers in Industry*, vol. 133, dec 2021. doi: 10.1016/j.compind.2021.103528.

[66] M. Cakir, M. A. Guvenc, and S. Mistikoglu, "The experimental application of popular machine learning algorithms on predictive maintenance and the design of IIoT based condition monitoring system," *Computers and Industrial Engineering*, vol. 151, p. 106948, 2021. doi: 10.1016/j.cie.2020.106948.

[67] T. Zhou, D. Tang, H. Zhu, and Z. Zhang, "Multi-agent reinforcement learning for online scheduling in smart factories," *Robotics and Computer-Integrated Manufacturing*, vol. 72, p. 102202, 2021. doi: 10.1016/j.rcim.2021.102202.

[68] B. Schmidt and L. Wang, "Predictive maintenance of machine tool linear axes: A case from manufacturing industry," *Procedia Manufacturing*, vol. 17, pp. 118–125, 2018. doi: 10.1016/j.promfg.2018.10.022.

[69] M. Kim, J. Jeong, and S. Bae, "Demand forecasting based on machine learning for mass customization in smart manufacturing," in *Proceedings of the 2019 International Conference on Data Mining and Machine Learning*. New York, USA: ACM, 2019, pp. 6–11. doi: 10.1145/3335656.3335658.

[70] H. Ren, D. Anicic, and T. A. Runkler, "The synergy of complex event processing and tiny machine learning in industrial IoT," in *Proceedings of the 15th ACM International Conference on Distributed and Event-based Systems*. New York, USA: ACM, 2021, pp. 126–135. doi: 10.1145/3465480.3466928.

[71] Y. Luo, J. Zhang, and G. Luo, "Unmanned plant control and optimisation by real-time deep neural networks for power saving," in *Proceedings of the 2019 International Conference on Artificial Intelligence and Advanced Manufacturing*. New York, USA: ACM, 2019, pp. 1–6. doi: 10.1145/3358331.3358359.

[72] B. Mayer and K. M. Lackner, “Selection of an IoT platform: A framework for a two-stage multi-criteria decision making process,” in *2022 8th International Conference on Computer Technology Applications*. New York, USA: ACM, 2022, pp. 281–286. doi: 10.1145/3543712.3543750.

[73] M. Molan, J. Ahmed Khan, A. Borghesi, and A. Bartolini, “Graph neural networks for anomaly anticipation in HPC systems,” in *Companion of the 2023 ACM/SPEC International Conference on Performance Engineering*. New York, USA: ACM, 2023, pp. 239–244. doi: 10.1145/3578245.3585335.

[74] A. Nikitin and S. Kaski, “Human-in-the-loop large-scale predictive maintenance of workstations,” in *Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*. New York, USA: ACM, 2022, pp. 3682–3690. doi: 10.1145/3534678.3539196.

[75] P. Empl and G. Pernul, “A flexible security analytics service for the industrial IoT,” in *Proceedings of the 2021 ACM Workshop on Secure and Trustworthy Cyber-Physical Systems*. New York, USA: ACM, 2021, pp. 23–32. doi: 10.1145/3445969.3450427.

[76] J. E. S. Diaz and T. M. Rudolf, “Path Planning Based on an Artificial Vision System and Optical Character Recognition (OCR),” in *Proceedings of the 2nd International Conference on Control and Computer Vision*. New York, USA: ACM, 2019, pp. 33–37. doi: 10.1145/3341016.3341034.

[77] J. Chen, D. Van Le, R. Tan, and D. Ho, “BubCam: A vision system for automated quality inspection at manufacturing lines,” in *Proceedings of the ACM/IEEE 14th International Conference on Cyber-Physical Systems (with CPS-IoT Week 2023)*. New York, USA: ACM, 2023, pp. 12–21. doi: 10.1145/3576841.3585926.

[78] H. Ping, Y. Wang, H. Feng, L. Qiao, W. Chen, and D. Li, “Understanding data correlations in continuous casting systems for autonomous fixed weight cutting,” in *Proceedings of the 2019 3rd International Conference on Advances in Image Processing*. New York, USA: ACM, 2019, pp. 114–118. doi: 10.1145/3373419.3373427.

[79] F. Bayram, B. S. Ahmed, E. Hallin, and A. Engman, “A Drift Handling Approach for Self-Adaptive ML Software in Scalable Industrial Processes,” in *Proceedings of the 37th IEEE/ACM International Conference on Automated Software Engineering*. New York, USA: ACM, 2022, pp. 1–5. doi: 10.1145/3551349.3559495.

[80] L. J. D. Ochoa and T. M. Rudolf, “Flexible production cell applying artificial vision concepts and open source CNCs,” in *Proceedings of the 2019 2nd International Conference on Intelligent Science and Technology*. New York, USA: ACM, 2019, pp. 51–55. doi: 10.1145/3354142.3354152.

[81] A. Machidon and V. Pejović, “Enabling resource-efficient edge intelligence with compressive sensing-based deep learning,” in *Proceedings of the 19th ACM International Conference on Computing Frontiers*. New York, USA: ACM, 2022, pp. 141–149. doi: 10.1145/3528416.3530230.

[82] M. H. Rais, Y. Li, and I. Ahmed, “Spatiotemporal G-code modeling for secure FDM-based 3D printing,” in *Proceedings of the ACM/IEEE 12th International Conference on Cyber-Physical Systems*. New York, USA: ACM, 2021, pp. 177–186. doi: 10.1145/3450267.3450545.

[83] J. C. Kirchhof, J. Michael, B. Rumpe, S. Varga, and A. Wortmann, “Model-driven digital twin construction,” in *Proceedings of the 23rd ACM/IEEE International Conference on Model Driven Engineering Languages and Systems*. New York, USA: ACM, 2020, pp. 90–101. doi: 10.1145/3365438.3410941.

[84] R. Shah and S. Nagaraja, “Do we have the time for IRM?” in *Proceedings of the 20th International Conference on Distributed Computing and Networking*. New York, USA: ACM, 2019, pp. 496–501. doi: 10.1145/3288599.3295582.

[85] A. N. Khan, N. Iqbal, A. Rizwan, S. Malik, R. Ahmad, and D. H. Kim, “A Criticality-Aware Dynamic Task Scheduling Mechanism for Efficient Resource Load Balancing in Constrained Smart Manufacturing Environment,” *IEEE Access*, vol. 10, pp. 50 933–50 946, 2022. doi: 10.1109/ACCESS.2022.3173157.

[86] X. Liu, J. Li, H. Wang, W. Jia, J. Yang, and Z. Guo, “Design of an Optimal Scheduling Control System for Smart Manufacturing Processes in Tobacco Industry,” *IEEE Access*, vol. 11, pp. 33 027–33 036, 2023. doi: 10.1109/ACCESS.2023.3261883.

[87] X. Xin, S. L. Keoh, M. Sevegnani, M. Saerbeck, and T. P. Khoo, “Adaptive model verification for modularized Industry 4.0 applications,” *IEEE Access*, vol. 10, pp. 125 353–125 364, 2022. doi: 10.1109/ACCESS.2022.3225399.

[88] D. Divisi, G. Di Leonardo, G. Zaccagna, and R. Crisci, “Basic statistics with Microsoft Excel: a review,” *Journal of Thoracic Disease*, vol. 9, no. 6, pp. 1734–1740, 2017. doi: 10.21037/jtd.2017.05.81.

[89] J. H. Hsiao and K. C. Chen, “Network analysis of collaborative cyber-physical multi-agent smart manufacturing systems: Invited paper,” in *2019 IEEE/CIC International Conference on Communications in China, ICCC 2019*. IEEE, 2019, pp. 219–224. doi: 10.1109/ICCChina.2019.8855896.

[90] S. Samoili, M. L. Cobo, E. Gómez, G. De Prato, F. Martinez-Plumed, and B. Delipetrev, “AI WATCH. Defining Artificial Intelligence,” 2020. doi: 10.2760/382730.

BIOGRAPHIES OF AUTHORS

Santo Wijaya has been an IEEE member since 2019. He received a bachelor’s degree in physics engineering from the Institute of Technology of Bandung, Indonesia, in 2004 and an M.Eng. (Master of Engineering) in electrical engineering from Chulalongkorn University, Thailand, in 2010. He is currently a doctoral candidate in computer science at Bina Nusantara University, Indonesia. His research interests include deep learning for control systems, model-based control systems, cyber-physical systems, digital twins, and software engineering. He can be contacted at email: santo.wijaya@politeknikmeta.ac.id.

Lim Hermanto Rudy has been an R&D Department Head of Kunlene Group which is part of Salim Group and situated in China, he has been joining with the group since 2009. He received a bachelor's degree in Chemical Engineering from Parahyangan Catholic University, Bandung, Indonesia in 2005. He is currently an engineer candidate of engineer professional program (PPI). His current interests are applied polymer research, manufacturing digitalization, R&D management system. He can be contacted at email: chai_rudy@kunlene-yn.com.

Fransisca Debora has been a lecturer in the Industrial Engineering Program since 2015. She received a bachelor's degree in physics from Sriwijaya University, Palembang, in 2011 and an M.T. (master of engineering) in industrial engineering from Mercu Buana University, Jakarta, in 2019. Her current research interests are productivity and quality engineering. She can be contacted at fransisca.debora@ft.unsika.ac.id.

Rana Ardila Rahma has been a lecturer in the Industrial Engineering Program at Singaperbangsa Karawang University since 2022. She received a bachelor's degree in textile engineering from Bandung Polytechnic of Textile Technology in 2016 and a master's degree in industrial engineering and management from Bandung Institute of Technology in 2020. Her current research interests are inventory systems and production manufacturing systems. She can be contacted at rana.ardila@ft.unsika.ac.id.

Arief Ramadhan is a senior member of the IEEE Computer Science Society and an assistant professor at the School of Computing, Telkom University, Indonesia, where he has been a faculty member since 2023. He teaches and supervises doctoral dissertations on several topics, including business intelligence, information systems, enterprise architecture, information technology, gamification, e-business, e-tourism, e-government, e-learning, the metaverse, and data analytics. He can be contacted at arieframadhan@telkomuniversity.ac.id.

Yusita Attaqwa has been a lecturer in the Industrial Engineering Program since 2021. She received a bachelor's degree in animal husbanry from Padjadjaran University, Bandung, in 2018 and Master of Engineering (M.T.) in industrial engineering from Diponegoro University, Semarang, in 2020. Her current research interests are ergonomy and quality engineering. She can be contacted at email: yusita@politeknikmeta.ac.id.